

**ASSESSMENT OF SPATIO-TEMPORAL CHANGE OF LAND-
USE AND LAND-COVER IN IB VALLEY COALFIELD USING
REMOTE SENSING AND GIS**

**A THESIS SUBMITTED IN PARTIAL FULFILLMENT OF THE
REQUIREMENTS FOR THE DEGREE OF
BACHELOR OF TECHNOLOGY**

By

RAMESH KUMAR (111MN0074)

ANUSHRAV GANTAYAT (111MN0567)



DEPARTMENT OF MINING ENGINEERING

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ROURKELA-769008

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UNDER GUIDANCE OF: ASST. PROF. NIKHIL PRAKASH



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DEPARTMENT OF MINING ENGINEERING

NATIONAL INSTITUTE OF TECHNOLOGY, ROURKELA

CERTIFICATE

This is to certify that the thesis entitled “**ASSESSMENT OF SPATIO-TEMPORAL CHANGE OF LAND-USE AND LAND-COVER IN IB VALLEY COALFIELD USING REMOTE SENSING AND GIS**” submitted by Ramesh Kumar in partial fulfillment of the requirements for the award of Bachelor of Technology degree in Mining Engineering at National Institute of Technology, Rourkela is an authentic work carried out by him under my supervision and guidance.

To the best of my knowledge, the matter embodied in the thesis has not been submitted to any other University/Institute for the award of any Degree or Diploma.

Date:

Prof: Nikhil Prakash

Dept. of Mining Engineering

National Institute of Technology

Rourkela, Odisha-769008

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RAMESH KUMAR

DATE:

Dept. of Mining Engineering

National Institute of Technology

Rourkela, Odisha – 769008

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ABSTRACT

Availability of vast coal reserve along with nearby water reservoirs transferred Ib Valley into one of the prominent mining and industrial zone in Western Odisha. Here, the major portion of coal production is achieved through mechanized opencast working and contributed 44.46 M.T. of coal in last financial year 2013-14 (www.mcl.gov.in, last accessed: 12/05/2015).

The present study focuses on the use of Remote Sensing and GIS as a tool for land use delineation and change detection in Ib Valley coalfields in last three decades. LANDSAT TM 1989, LANDSAT 7 data for 2000 and 2003, LISS –III data for 2012 and LANDSAT-8 data for 2015 were used for this study. The classification map with five prominent five land use/land cover categories was generated with the help of ArcGIS and ERDAS using various indices and visual image interpretation techniques.

The comparative analysis of the classification maps in different time periods shows that the total loss in vegetation cover between 1989 and 2015 is about 1434 km² and increase in mining area is about 30 km². Though the water body has decreased but still there is not much difference. The total increase in settlements amounts to 119 km². Thus it is clear that large scale mining leads to massive deforestation as can be seen in Ib Valley area.

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CHAPTER 01

INTRODUCTION

1.1 BACKGROUND TO THE STUDY

Land use / land cover classification describes the spatial distribution of features like forest, water bodies, residential area, etc. on the Earth surface. This is not constant for an area and changes rapidly with time, depending on the local human and natural factors. Unlike the prevalent perception, a change in LU/LC do not necessarily imply degradation of the land and environment. However, changes in land use may affect the climate and biosphere, if the resulting land cover changes are affecting the biodiversity, water balance, socio-economic condition and other activities (Riebsame et al., 1994). A timely and accurate analysis of these changes over time is an important component in understanding the interaction of human activities with the environment. This will enable us to efficiently manage our available limited natural resources and maintain a sustainable environment (Lu et al., 2004). Land use refers to human activities and the various uses which are carried on land to fulfill the needs of human being. Whereas land covers refers to natural vegetation, water bodies, built-up area, rock/soil, artificial cover, and others noticed to the land. Land cover representing the hookup of biotic and abiotic components on the earth's surface are the decisive properties of the earth system. It reflects the biophysical state of the earth's surface.

Change detection is the process of identifying differences in the state of an object or phenomenon by observing it at different times (Singh, 1989). The land use/land cover pattern of a region is an outcome of natural and socio – economic factors and their utilization by man in time and space. Hence, information on land use / land cover is essential for the selection, planning and implementation of land use and can be used to meet the increasing demands for basic human needs and welfare. This information also assists in monitoring the dynamics of land use resulting out of changing demands of increasing population (Zubair, 2006).

The mining industry has grown and spread wide rapidly to keep pace with growing demands. But this industry straggle often encroach upon productive agricultural and essential forest land. Hence this overwhelming growth of mining activities generally has a negative impact on the environmental health of a region. Usually, minerals occur under features such as forest area or agricultural land and thus mining activities are to be undertaken at the cost of degrading this forest or agricultural area. Therefore, it is necessary to supervise such changes on the earth's surface. Rapid growth of mining activities can also be attributed as one of the reasons for decrease and degradation of land. The mining of natural resources is invariably associated with land use and land cover changes. Modern techniques of surface mining using heavy earth moving machinery (HEMM) can produce huge alterations in land cover, both ecologically and hydrological. Mining of coal both surface and subsurface causes damage to the flora, fauna, soil biological properties and hydrological relations of the systems. Opencast mining, which is being given greater importance due to high output and safer with high capital investment. Coal mining operations generally, changed the natural topography of the area. Large pits are left after mining and large amounts of overburden material excavated during mining is dumped in the vicinity of the mine sites and continuous re-handling of the overburden dumps further modifies the general landscape of the area. Degradation of forests during mining operation is invariably accompanied by an extensive damage and loss to the forest ecosystem and wildlife habitat. The overburden of coal mines when dumped in unmined areas creates mine spoils which ultimately affects the surrounding vegetation. This project is a collaborative effort by me along with my colleague, Ramesh Kumar, to analyze the temporal land use / land cover changes in Ib Valley coalfield from 1989 to 2015. In the present study 5 different satellite images of Ib valley coalfields belonging to 1989, 2000 and 2003 2012 2015 are used to carry out change detection analysis. The land use and land cover maps for all these five temporal are created by taking

into account the various major components that have been affected by the mining activities in Ib Valley. The majority of changes are identified over water bodies, built-up areas, coal mining area, forests & non vegetation –non urban area.

Studying changes in land-use pattern using remotely-sensed data is based on the comparison of time-sequential data, change detection using satellite data can allow for timely and consistent estimates of changes in land-use trends over large areas, and has the additional advantage of ease of data capture into a GIS. It also offers the most economical means of assessing environmental impact of the developmental processes, monitoring of an ecosystem and generation of suitable action plans for sustainable development. Mining operations, which involve minerals extraction from the earth's crust tends to, make a notable impact on the environment, landscape and biological communities of the earth. The use of remote sensing coupled with Geographic Information Systems (GIS) provide the most accurate means of measuring the extent and pattern of such changes in landscape conditions over time. Coal mining areas are largely located in the vicinity of Ib River. Mining pits are interpreted on FCC by its black tone, medium to smooth texture having linear to curvilinear pattern and irregular shape. Monitoring the locations and distributions of land-cover changes is important for establishing linkages between policy decisions, regulatory actions and subsequent land-use activities.

Different rationing technique is applied to identify the change. Ratios also provide information and subtle spectral-reflectance or color differences between surface materials that are often difficult to detect in a standard image. It is also useful for discriminating between soils and vegetation. Change detection analysis is a versatile tool that can be used in mapping the differences land cover pattern in many fields like urban area, forests, river, lakes and mining. Along with calculating change area of each land feature NDVI, NDBI, NDWI etc. values can also be used to give a clearer picture of the changing scenario. Unlike

typical classification assessment that requires only single date validation data, change detection validation data must be available for multiple dates to provide sufficient change event documentation. So we have faced some difficulties to get data of different desired time periods.

1.2. OBJECTIVE

Present study was undertaken to analyze the extent of human-induced LU/LC transformation in the mining affected areas of Ib Valley by interpreting temporal remote sensing data using GIS.

- To create a land use-land cover classification scheme and to generate statistical data on land consumption by quarries and reduction of forest area.
- Change in built-up area due to urbanization over last two decades since 1989.
- A detailed understanding of the impact of mining on changes in land use/land cover pattern by analyzing the assessment of spatio-temporal change.

1.3 ORGANISATION OF THESIS

Chapter 1: Gives an insight to the selection of the topic and its importance. The objectives and scope of the present work is identified in this chapter.

Chapter 2: A brief idea about the literature review that has been performed before undertaking the project.

Chapter 3: Reviews the interpretation techniques used in the present study either visual image interpretation or band rationing techniques for land use mapping of the study area.

Chapter 4: It gives an insight of study area and the technical details of data sets used for conducting the mapping.

Chapter 5: A brief description of methodology followed.

Chapter 6: It presents a thorough discussion on the statistical results obtained from the land cover land use map.

CHAPTER 02

LITERATURE REVIEW

Tripathy (2010) analyzed the land use changes from 1929 to 2009 by utilizing satellite imagery of TM maps information for 1990, 1999 and Google earth imagery for 2009 and Survey of India topographic maps have been considered to generate the sheet. The study has created a land use/ land cover map of Korba area of Chhattisgarh for different time periods, here imageries of five distinction period taken into account (1929, 1970, 1999, 2005, 2009) point of time with a goal to identify the progressions that have occurred especially in the urban area, mining range, water bodies, and forests. From the result it can be concluded that amid a period of this 80 years forest area diminished from 4622.82 km² in 1929 to 2241.66 km² in 2009. The agriculture area expanded amid the period 1929-1970 demonstrating that non forest area was changed over into farming land amid this period. From 1970 onwards, mines and barren region expanded from nil to 527.72 km² in 2009. Amid the period from 1929 to 2009 mining and barren area expanded by 7.98% though forest area saw an abatement. The variation in land cover was maximum for forest land as compared to others. Water body expanded amid this period. There was an increment in agriculture area because of expansion in populace. Henceforth, such activities must be controlled to minimize the adverse impacts. The discoveries of the study could be valuable in formulating the Environment Management Plan for the area.

Khan and Javed (2012) conducted a study on Singrauli coalfields area as it is one of the coal mining region where huge scale mining activities are going on. In this study multi-spectral/multi-temporal information of Indian Remote Sensing Satellite (IRS) LISS II geocoded (FCC) of two different time periods were used dated 4th May 1993 and LISS III of 4th May 2010 for thematic mapping. Survey of India topo sheet 63L/12 on scale 1:50,000 were utilized to create base map which was overlaid on the FCC for land use/ land cover

mapping through visual understanding. Visual understanding of satellite imagery prompted the detection of 15 land use/land cover classifications for example dense forest, cultivated land, open forest, mining pits, wasteland, overburden dumps etc. . The ground truth check was done in key regions to redress the errors in created maps and after that land use/ land cover maps were finished. It has been recognized that the principle drivers which has expanded the rate of progress in land use/ land cover are primarily coal mining & industrial extension.

Kumar and Pandey (2013) had done an assessment of spatio-temporal land use/land cover changes in South Karanpura coal mine and surrounding area was done amid the period from 1992 to 2009. Land use/ land cover maps for the year 1992, 2004 and 2009 were produced through the visual understanding of ETM and IRS -1D LISS-III satellite images. The major changes are identified over agricultural area, coal mining areas and forests. The study uncovered that coal mining zone extended from 10.06 sq. km in 1992 to 21.29 sq. km in 2004 and further reduced to 19.40 sq. km by the year 2009 because of lessening of coal hold and decrease in the coal creation showing 92.84% zone increment in coal mining induced land utilization changes fundamentally to the detriment of cropland (-38.67%) and dense forest (-71.85%). The coal mining range which was 10.06 sq. km in 1992 (3.6%) increments to 21.29 sq. km in 2004 (7.68%) and further reduced to 19.40 sq. km (6.9%) by the year 2009.

Singh and Mahanto (2013) had studied the land use/ land cover changes in the Jharia coalfield. Extensive growth of coal mining in the region is a major concern for sustainable environment. The study was done to identify land use changes between 1995 to 2008 utilizing topographical maps created by GSI, aerial photos & satellite images of IRS LISS IV

MX satellite imagery of NRSC. Hyderabad. The information was received in 12 sheets covering the whole coalfield alongside computerized TIFF position. The land use changes had been recognized by image processing system ERDAS IMAGING 9.3, ArcGIS 9.3. Land use changes had been identified by image differencing & image rationing of NDVI pictures. It can be concluded from the study that rapid mining, extension of urban settlements diminish vegetation spreads lead to adverse effect of mining to environment in the Jharia coal field area.

Choudhury (2012) in his study concentrated on the utilization of Remote Sensing and GIS as a tool for change detection & analysis land use pattern of Talcher, Odisha a well-known hub of coal mining which contributes about 16.3% of the nation's aggregate store. The land cover changes in Talcher area was analyzed for the three unique years – 1973, 1990 and 2009. The LANDSAT MSS imagery for 1973 and LANDSAT TM imagery for the years 1990 and 2009 were utilized for the study. Land use land cover maps, NDVI maps of the range for the given time period had been made. From the study it was observed that the decrease in forest between 1973 and 2009 is around 43 km^2 and increment in mining range is around 34 km^2 . In spite of the fact that the water body has diminished yet at the same time there is very little distinction. The aggregate increment in settlements adds up to 28 km^2 . Hence it can be concluded that substantial scale mining causes large scale deforestation as can be seen in Talcher territory.

CHAPTER 03

INTERPRETATION

TECHNIQUES

3.1 VISUAL IMAGE INTERPRETATION

Perceiving targets is the way of data extraction through interpretation. The distinction between surface features are done by analyzing any, or all, of the visual image interpretation components which includes tone, shape, size, pattern, texture, shadow, and association as explained in Table 3.1. Visual interpretation using these components is a regular practice of our daily lives. Analyzing satellite imagery on the weather report, or taking after rapid pursues by perspectives from a helicopter are every single commonplace illustration of visual image interpretation.

Table 3.1: COMMON ELEMENTS OF IMAGE INTERPRETATION, Bhatta (2008)

S No.	Elements of Image Interpretation	Description
1.	Tone	It refers to the relative brightness of color of objects in an image. The continuous grey scale varying from white to black is called hue/tone. In panchromatic image any object will reflect its unique tone according to the reflectance.
2.	Color	Color images can be obtained by using color films & color infrared films. We may use color combination technique to create color composite images from the individual bands of multispectral image data to obtain specific information depending on the emulsion of film or the filter used.
		It refers to the general form, configuration or outline of individual objects which gives very distinctive clue for

3.	Shape	interpretation. Natural features, such as forest edges, are generally more irregular than manmade settlements.
4.	Size	It is a function of scale. A proper photo scale should be selected as per the requirement of interpretation. A quick approximation of target size can direct interpretation to an appropriate result more quickly. Most commonly used parameters are perimeter, area & volume.
5.	Pattern	It refers to the spatial arrangement of visibly discernible objects. On an image it usually illustrates a functional relationships between the individual features that compose the pattern. Typically an orderly repetition of similar tones and textures will produce a distinctive pattern such as urban streets.
6.	Texture	It refers to the frequency of tonal variation in an image which is an important elements for distinguishing features in image which are too small to resolve individually. It determines the overall smoothness or coarseness of image.
7.	Shadow	It is usually a visual obstacle for image interpretation. Bur many case helpful in interpretation. As it may provide an idea of the profile and relative height of targets which may make identification easier by provide profile views of certain features that can aid their

		identification. It gives the information of shape as well as height in some instance.
8.	Association	It takes into account the relationship between other recognizable objects or features in proximity to the target of interest. The identification of features that one would expect to associate with other features may provide information to facilitate identification. In the example given above, commercial properties may be associated with proximity to major transportation routes.

When this information extraction from remotely sensed imageries are carried out manually, it is referred as visual interpretation whereas when this interpretation is carried out by automated processes in a computing system, it is referred as digital image interpretation.

3.2. BAND RATIONING TECHNIQUES

Proportion changes of the remotely detected information can be connected to decrease the impacts of environment. Proportions additionally give special data and spectral reflectance or color contrasts between surface materials that are frequently hard to recognize in a standard picture. It is likewise helpful for separating soils and vegetation.

Table 3.2 IDENTIFICATION OF LULC FEATURES USING BAND RATIOING TECHNIQUES: (<http://www.murraystate.edu/qacd/cos/geo/gsc641/1997/rahman/>)

Band Ratios	Description
$\frac{\text{Band 3}}{\text{Band 4}}$	This proportion has characterized desolate terrains and urban region remarkably. Be that as it may, it couldn't characterize water body, forests and croplands.

$\frac{\text{Band 4}}{\text{Band 3}}$	This ratio recognized vegetation, water and croplands. It has improved forests, barren grounds. Since forests or vegetation displays higher reflectance in close IR area (0.76 -0.90 m) and solid absorption in Red band (0.63-0.69 m).
$\frac{\text{Band 5}}{\text{Band 7}}$	This proportion divided land and water particularly. Since soils display solid ingestion in the band 7 (2.08 -2.35 m) and high reflectance in band 5 (1.55 - 1.75 m), soil has been upgraded in this proportion. Area has showed up as lighter tone and water showed up as dull tone.
$\frac{\text{Band 5}}{\text{Band 4}}$	It has divided water body from forests, infertile terrains and vegetation. In this ration water has showed up as dull tone and forests, infertile grounds, exposed croplands all have shown brighter tone.
$\frac{\text{Band 5}}{\text{Band 7}}$	It has divided water body from terrains (soils). It has likewise improved the presence of moisture in croplands. All water bodies showed up as dark tone. Both band 5 and band 7 are delicate to moisture content variety in soils and vegetation.
$\frac{\text{Band 3}}{\text{Band 5}}$	This proportion upgrades barren grounds, thruways, road designs inside the urban zones and urban assembled up or established territories. It couldn't upgrades the clear water however it enhanced turbid water. This proportion is valuable for analyzing differences in water turbidity. Infertile lands, and built up territories have showed up as lighter tone whereas forest, water body and croplands showed up as dark tone.

3.3 BAND INDICES

The accessibility of remote sensing information significantly helped mapping and overseeing yet its commitment in evaluation of spectral changes has been broadly utilized and demonstrated valuable. In any case, due to different components such examination did not yield adequate results. One of such circumstances is the confusion among different land cover classes. To overcome such confusion and to enhance land cover characterization results, diverse strategies have been utilized and proportion are among those. These indices do help dividing different complex land covers, yet at the same time differentiating some land covers creates problems.

3.3.1 VEGETATION COVER

Normalized Difference Vegetative Index (NDVI)

Live green plants absorb solar radiation in the photo synthetically active radiation (PAR) spectral region, which they use as a source of energy during the photosynthesis. Leaf cells have likewise advanced to scramble solar radiation in the near infrared spectral area, clouds and snow have a tendency to be somewhat brilliant in the red (and also other visible wavelengths) and very dark in the near infrared. The pigment in plant leaves, chlorophyll, strongly absorbs visible light (from 0.4 to 0.7 μm) for utilization in photosynthesis. The cell structure of the leaves, then again, emphatically reflects near infrared light (from 0.7 to 1.1 μm). The more leaves a plant has, the more these wavelengths of light are influenced.

$$NDVI = \frac{NIR-RED}{NIR+RED} \dots\dots\dots(3.1)$$

Where, NIR= Near Infra-red

These spectral reflectance are themselves proportions of the reflected over the incoming radiation in every spectral band exclusively, consequently variable values somewhere around 0.0 and 1.0. By design, the NDVI itself accordingly shifts between -1.0 and +1.0. It ought to be noticed that NDVI is practically, however not directly, proportionate to the basic infrared/red proportion (NIR/VIS). The benefit of NDVI over a basic infrared/red proportion is accordingly by and large restricted to any possible linearity of its practical association with vegetation properties (e.g. biomass). NDVI is practically and directly proportional to the proportion $\text{NIR} / (\text{NIR} + \text{VIS})$, which extends from 0 to 1 and is along these lines never negative nor boundless in reach. Be that as it may, the most vital idea in the comprehension of the NDVI mathematical equation is that, notwithstanding its name, it is a transformation of a spectral ratio (NIR/VIS), and it has no functional relationship to a spectral difference (NIR-VIS).

PERFORMANCE AND LIMITATIONS

It can be seen from its mathematical definition that the NDVI of a territory containing a thick vegetation canopy will have a tendency to positive qualities (say 0.3 to 0.8) while clouds and snow fields will be described by negative estimations of this index. Utilizing the NDVI for quantitative estimations creates different issues that may genuinely constrain the real convenience of this index in the event that they are not legitimately tended to. Also, the NDVI has had a tendency to be over-utilized in applications for which it was never designed. Standing water (e.g., oceans, seas, rivers and lakes) which have a rather low reflectance in both spectral bands and hence result in very low positive or even slightly negative NDVI values. Similarly Soils generally show a near-infrared spectral reflectance somewhat longer than the red, hence tend to generate rather small positive NDVI values (say 0.1 to 0.2). Users of NDVI have had a tendency to estimate number of vegetation properties from the estimation of this index. Common illustrations incorporate the Index, biomass, chlorophyll

concentration in leaves, plant efficiency, fractional vegetation spread, and so on. Such relations are frequently determined by correlating space-inferred NDVI values with ground-measured estimations of these variables. This methodology raises further issues identified with the spatial scale connected with the measurements, as satellite sensors always measure radiation amounts for regions generously bigger than those examined by field instruments. The reflectance estimations ought to be in respect to the same area and be procured simultaneously. This may be difficult to accomplish with instruments that acquire different spectral channels through various cameras or focal planes. Mis-registrations of the spectral pictures may prompt significant mistakes and unusable results. Likewise, the figuring of the NDVI quality ends up being touchy to various unwanted components including.

Consequently, the NDVI ought to be utilized with caution. In any quantitative application that requires a given level of accuracy, all the bothering figures that could result errors or uncertainties of that order should be considered. Later forms of NDVI datasets have tried to record for these complicating elements through processing. Various subsidiaries and different options for NDVI have been proposed in the scientific writing to address these constraints, including the Perpendicular Vegetation Index (PVI) the Soil-Adjusted Vegetation Index the Atmospherically Resistant Vegetation Index and the Global Environment Monitoring Index. Each of these endeavored to incorporate intrinsic corrections. Since the advancement of NDVI, different indices have been created in order to separate land spread from remotely sensing information. The idea for creating such indices is to recognize the weakest and strongest reflectance band from multi-spectral data. At that point, taking into account the recognized weakest and strongest bands, indices are developed separately to upgrade a specific area spread class. The yield of these indices created through

routine methodology improved required land cover over extensive variety of DN values and suppresses rest of the others.

Soil Adjusted Vegetative Index (SAVI)

The shortcoming of the PVI is the suspicion that there will be one and only kind of soil underneath the vegetation. Then again, this is not generally the situation, as there are situations where a mixture of soil sorts (a mixture of soil and rocks for instance) can be found inside a little territory. Huete (1988) proposed the Soil-Adjusted Vegetation Index (SAVI) to manage this issue as specified in Eq-3.2. SAVI is a hybrid between a proportion index (NDVI) and a perpendicular index (PVI). Its equation similar to the previous. There are different vegetation indices to upgrade vegetation data in remote sensing imagery generally by rationing a near infrared (NIR) band to a red band. This takes advantage of the high vegetation reflectance in NIR spectral range such as TM band 4 and high pigment absorption of red light, such as TM band 3 (Jensen, 2000).

Normalized Difference Vegetation Index (NDVI), Utilizing SAVI to highlight vegetation features because of its point of interest over NDVI when connected in a territory with low plant cover, for example, the urban regions. SAVI can work in the region with plant cover as low as 15 percent, while NDVI can just work adequately in the region with plant cover over 30 percent The SAVI is computed utilizing the accompanying mathematical statement (Huete, 1988)

$$SAVI = \frac{NIR-RED}{(NIR+RED+L) \times (1+L)} \dots\dots\dots(3.2)$$

L is a correction factor and its value is reliant on the vegetation spread. For aggregate vegetation spread it gets an estimation of zero, viably transforming SAVI into NDVI. For

low vegetation spread, it gets the estimation of 1. Huete (1988) recommended that the estimation of 0.5 is utilized when vegetation spread is obscure, as 0.5 signifies to middle of the road vegetation spread.

3.3.2 WATER BODIES

Water bodies comprises of all surface water bodies viz. irrigation tanks, reservoirs, lakes, and streams. There will be variety in spatial degree of these features as an element of rainfall amounts, intensity of rainfall and so on over season/ year. In expansion to these surface water bodies, there will be other representations of water surface that may show up because of flood inundations, standing water in rice crop regions amid transplantation stages, and so forth. These segments are seasonal and may exist for little time period (days/weeks).

Normalized Difference Water Index (NDWI)

In a band-proportion methodology utilizing two multispectral groups one is taken from visible wavelengths and is divided by the other typically from close infrared (NIR) wavelengths. Accordingly, vegetation are smothered while water features are upgraded. Nonetheless, the method can suppress non-water features however not uproot them, and along these lines the NDWI was proposed by McFeeters 1996 as given in Eq- 3.3 to attain to this objective.

This index is intended to augment reflectance of water by utilizing green wavelengths; minimize the low reflectance of NIR by water features and exploit the high reflectance of NIR by vegetation and soil characteristics. Subsequently, water highlights have positive qualities and accordingly are upgraded, while vegetation and soil for the most part have zero or negative qualities and therefore suppressed. (McFeeters 1996).

$$NDWI = \frac{GREEN - NIR}{GREEN + NIR} \dots\dots\dots(3.3)$$

The determination of these wavelengths boosts the reflectance properties of water. That is:

- Maximize the ordinary characteristics reflectance of water highlights by utilizing green wavelengths.
- Minimize the low reflectance of NIR by water features and
- Maximize the high reflectance of NIR by vegetation and soil characteristics.

Notwithstanding, the use of the NDWI in water districts with a built up area foundation does not accomplish its objective obviously. The extracted water data in those area was frequently blended with built up area noise. This implies that numerous built up area features have positive values in the NDWI image.

3.3.3 URBAN AREA

Remotely sensed imagery is a kind of information that is perfect with the detecting and mapping of changes in built up and barren land inside urban ranges as the effects of populace development and urbanization increment. The utilization of presently accessible remote sensing indices, however, has a few constraints concerning recognizing built up and barren land in urban territories. An urban part covering a little territory can't be recognized in the low- to medium spatial determination information on the grounds that it can blend with different parts inside a pixel. Since high spatial determination information have been expensive, numerous scientists have focused on enhancing the accuracy of urban area spread grouping utilizing medium-spatial determination remote sensing information.

Urban spatial ranges have extended in a quickened velocity amid the most recent five decades, and rates of urban populace development are higher than the general development in many nations in light of the fact that urban territories are the locus of financial action and transportation hubs (Masek et al., 2000). Extended urbanized Cranges infringed on encompassing important common grounds, for example, paddy fields, forestlands, or

wetlands (Xu et al.2000). Urban territories are ruled by manufactured up terrains with impenetrable surfaces, and accordingly the change of the nature lands into these impenetrable constructed up grounds may have noteworthy effects on the biological community, hydrologic framework, biodiversity, and neighborhood atmosphere which can bring about the negative aspects, for example, the urban heat island.

Normalized Difference Built-up Index (NDBI)

Because of urban complexity, spectral reflectance may speak to the mix of a few area spreads called as blended pixel. All the more over supervised classification is arduous and has a high likelihood of misclassification between uncovered soil and urban area, since both area spreads can have comparable spectral signatures at a few spots. Built-up Land is the area covered by settlements identified with the populace. The urban sprawl and corresponding development in populace is by and large identified with decline in cropland and grassland ranges. Built-up area is distinguished on false shading composite (FCC) by its cyan - light grey tone, coarse composition scattered pattern and irregular outline. Built up land was categorized into three types viz; urban, industrial and rural settlements.

The advancement of the index was in view of spectral response of built-up lands that have higher reflectance in MIR wavelength range than in NIR wavelength range. Nonetheless, this is not always. A few studies demonstrated that the reflectance for specific sorts of vegetation over the band pass of TM5 expanded as leaf water substance decreased (Cibula et al., 1992; Gao, 1996). The drier vegetation can even have higher reflectance in MIR wavelength range than in NIR range (Gao, 1996), subsequent in positive values in NDBI for these plants. NDBI can be calculated as per Eq-3.4. This study additionally found that the numerous vegetated regions have positive NDBI values.

$$NDBI = \frac{MIR - NIR}{MIR + NIR} \dots \dots \dots (3.4)$$

Where MIR= Mid Infra-red

Normalized Difference Barren area Index (NDBaI)

As indicated by Herold et al. (1989), the reflectance estimations of built up ranges are higher because of the more drawn out sensor wavelengths. The NIR wavelength, which compares to band 4 in Landsat ETM+ and band 5 in SWIR, is connected with a high differentiation level for identifying built up and barren area territories. Moreover, in groups 4 and 5, there is an inverse reflectance proportion regarding distinguishing built up or barren area ranges contrasted with vegetation. Vegetation has a high reflectance in band 4, however the reflectance of built up or barren land in band 4 is low. Conversely, in band 5, there is high reflectance when recognizing built up regions contrasted and vegetated zones. NIR and SWIR were utilized for mapping built up ranges in a study at the point when adding to the NDBI. Zhao and Chen used Landsat ETM+ band 5 (SWIR) and band 6 (TIR) to produce the NDBaI. The NDBaI is an index used to guide barren area ranges and is calculated according to Equation 3.5. As per Weng the usage of TIR channels is exceptionally viable for mapping built up zones in view of a low albedo, which eliminates the impact of shadows and water, while a high albedo exhibits manufactured up and uncovered area territories clearly. The TIR channel likewise shows an abnormal state of complexity for vegetation.

$$NDBaI \frac{MIR - TIR}{MIR + TIR} \dots \dots \dots (3.5)$$

Where, TIR = Thermal Infra-red

Enhanced Built-Up and Bareness Index (EBBI)

The utilization of at present accessible remote sensing indices, in any case, has a few constraints as for recognizing built up and barren land in urban ranges. The Enhanced Built-

Up and Bareness Index (EBBI) has the capacity for mapping built-up & barren land utilizing a solitary computation. ne of the principle issues in mapping urban territories is surveying the adjustment in area utilization from non-residential to residential. NDBI and UI are in view of the high speed mapping of built up or barren area territories. but these two indices are not able to check the distribution of built up versus barren area The inability was because of the high complexity of spectral response to vegetation, barren land, and built up territories, especially regarding the pixel mixes in regions with heterogenic items.

By consolidating the NIR, MIR, and TIR (Landsat ETM+ groups 4, 5, and 6) wavelengths, the subtraction of band 4 from band 5 will bring about positive qualities for barren & built-up pixels and will bring about negative qualities for vegetation. Also, a summation of band 5 and band 6 will bring about higher qualities pixel for built up and uncovered area than for vegetation. The distinction between the subtraction of band 4 from band 5 and the summation of band 5 and band 6 will bring about for all intents and purposes 0,water pixels and also negative qualities for vegetation and positive qualities for manufactured up and fruitless pixels. This result takes into consideration simple recognizing assembled up and uncovered area ranges. The EBBI applies a root function to cluster the numbers that contrast identical objects based on the different levels of reflectance values. To obtain an index value of $-1 \sim 1$, the multiplied factor is divided by ten. The EBBI is calculated from the image data using the Equation -3.6.

$$EBBI = \frac{(MIR - NIR)}{10 \times \sqrt{(MIR + TIR)}} \dots \dots \dots (3.6)$$

CHAPTER 04

STUDY AREA

&

DATA SETS USED

4.1 STUDY AREA

The massive deposits of coal in vicinity of Hirakud reservoir have made Ib Valley-Jharsuguda range as the most appealing and comprehensive destination for mineral based commercial ventures. The area is a perfect site for establishment of thermal power plants and iron & steel industries. Ib Valley has attracted individuals from different regions of Odisha during the last few decades because of its vast coal reserves. The valley is spread across Jharsuguda district and is approximately 140 KM from Rourkela city. Till date no noticeable temporal land-cover change assessment studies have been carried out in this region. Hence, it has been selected as our study area.

Coalfield of the Ib Valley area was first explored by Mr. V..Ball of Geological Survey of India (GSI). Some works were also done by Mr.W.King during 1884-86. Further work was undertaken by Geological Survey of India. During 1977 Central Mine Planning Design Institute Ltd. (CMPDI) entrusted the Directorate of Mining & Geology (Govt. of Orissa) for detail exploration. IB Valley Coalfield was first discovered by B N Railway while constructing bridge over Ib river in the year 1900. M/S Himgir Rampur Coal Company opened colliery in the year 1909. Many more mines were opened in the year 1940, 1954 and after the nationalization of coal mines the mines came under WCL. Later on it came under South Eastern Coalfields Limited (SECL) and then under Mahanadi Coalfields Limited (MCL) in the year 1992 after its formation. Production of this field was 0.55 M.T. in 1972-73 which has increased upto 46.467 M.T. in the year 2013-14.

(<http://www.mcl.gov.in/Others/ecoalfields.php>)

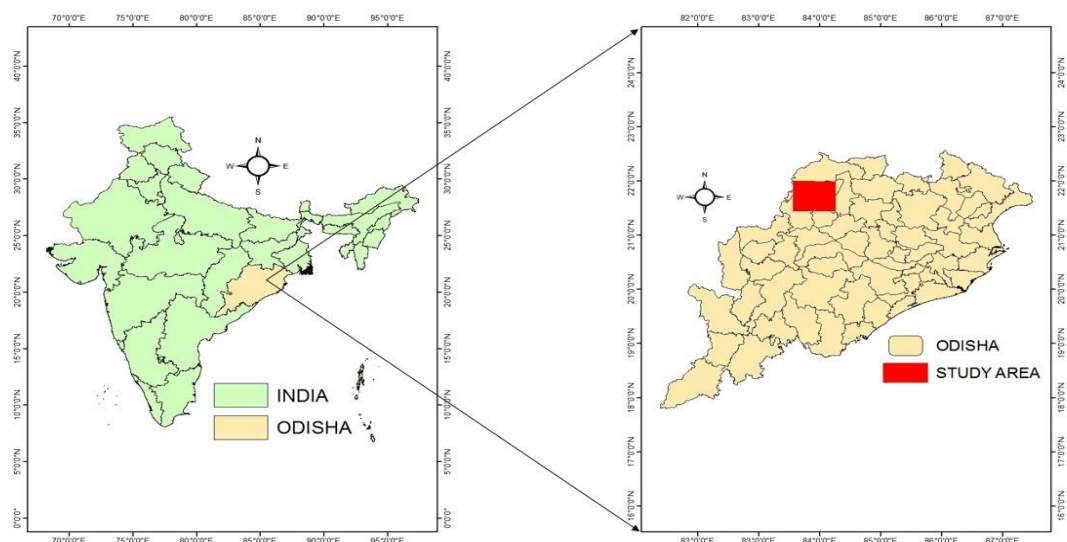


FIG 4.1 LOCATION OF IB VALLEY COALFIELD

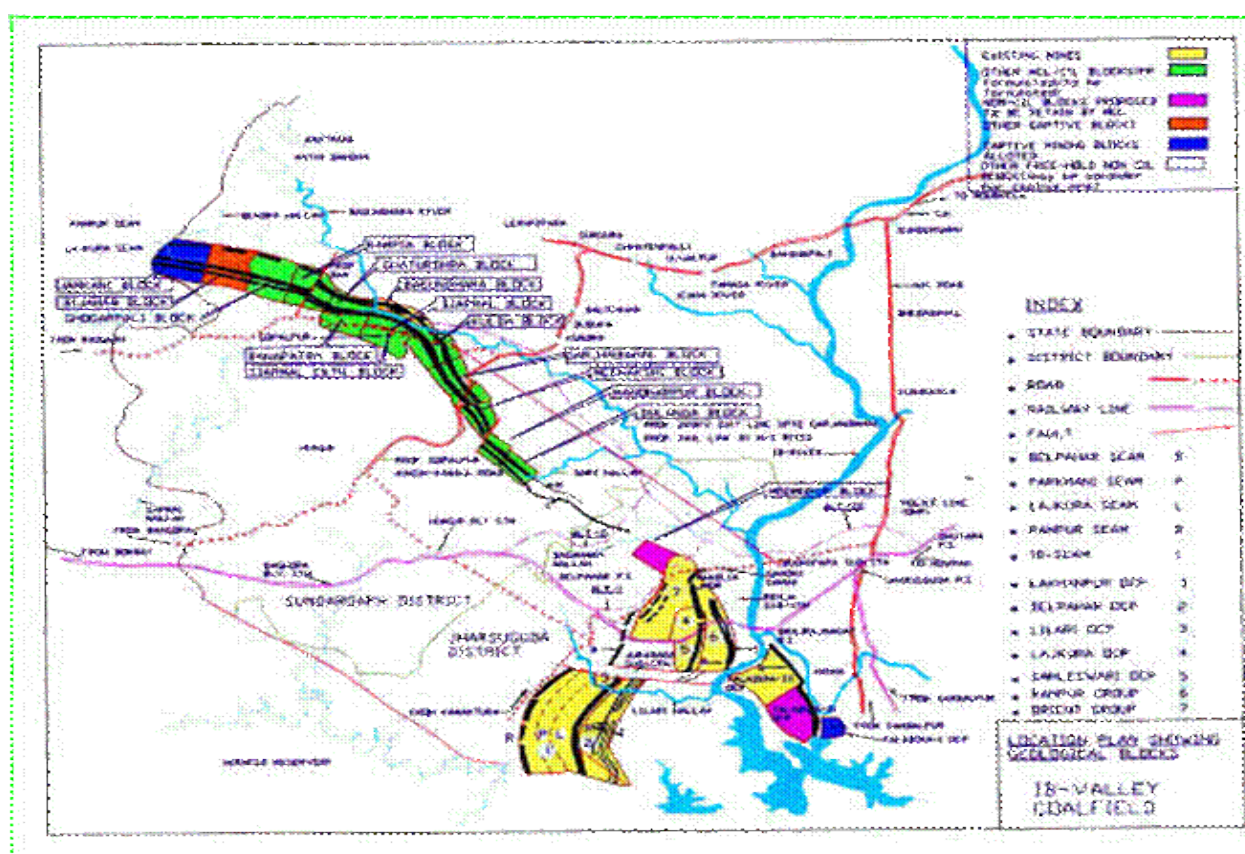


FIGURE 4.2 IB VALLEY COALFEILD (www.mcl.gov.in)

LOCATION

In Ib Valley Coalfield MCL operates five highly mechanized open cast mines – Lajkura Opencast Mine, (OCM) Samleswari OCM, Lilari OCM, Belpahar OCM, and Lakhanpur OCM. Ib Valley Coalfield lies between latitudes 21° 41'N and 22° 06'N and longitudes 83° 30'E and 84° 08'E. It covers an area of 1,375 square kilometers (531 sq mi). The IB Valley Coalfield derives its name from IB River, a tributary of Mahanadi River. The Himgir Coalfield lies on northwest is contiguous. The nearest Railway Station is Brajrajnagar on the Howrah-Mumbai main line. An all weathered road connects the coalfield with NH-200 which is connected with SH-10 & NH-6.

4.2 DATASETS USED

Table 4.1 DATA ACQUIRED AND SOURCE:

Platform/Scene ID	Sensor	Date	Spatial Resolution	Temporal Resolution	Source
Landsat TM/ etp141r45_5t19891031	TM	31/10/1989	30 m	16	USGS Global Visualization Viewer
Landsat - 7/LE71410452000103SG S00	ETM+	12/04/2000	30 m	16	USGS Global Visualization Viewer
Landsat - 7/LE71410452003063SG S00	ETM+	04/03/2003	30 m	16	USGS Global Visualization Viewer
IRS P6/ L3_SAT_8B_V1_83.5E2 1.5N_f44r10_04mar12	LISS-III	04/03/2012	23.5 m	24	Bhuvan ,NRSC
Landsat - 8/LC81410452015088L GN00	OLI - TIRS	29/03/2015	30 m	16	USGS Global Visualization Viewer

CHAPTER 05

METHODOLOGY

5.1 INTERPRETATION OF VARIOUS LAND COVER CLASS

The classes were demarcated for this present study are:

Built-up Area- It consists of areas of extensive man-made structures. Residential area viz cities, towns industrial complex takes precedence over others.

Vegetation cover- It is the area cover which demonstrates healthy vegetation like dense forest, dense cropland etc. Sparse vegetation with lower cutoff than the chosen threshold value are not classified as vegetation.

Water bodies- It comprises of all surface water bodies like reservoirs, lakes, and streams. There will be variety in spatial of these features as an element of rainfall amounts, and so on over season/ year.

Mining land-An area directly affected by mining induced activities are categorized as mining land. Overburden dump, coal stockpiles and mining pits are classified as mining area in this study.

Barren land- This is the demarcated area which are unclassified in the study. It comprises of areas without any prominent water bodies or mining land. Similarly it does not contain any dense vegetation or built up area according to the threshold chosen.

The criteria for identification of an object with interpretation elements is called an interpretation key which is a set of guidelines used to assist interpreters in rapidly identifying features. The image interpretation depends on the interpretation keys which an experienced interpreter has established from prior knowledge and the study of the current images. Generally, standardized keys must be established to eliminate the difference between interpreters. The eight interpretation elements, as well as the time the photograph is taken, season, film type and photo scale should be carefully considered when developing interpretation keys.

5.2 METHODOLOGY FLOW CHART

Figure 5.1 shows the methodology adopted for this study.

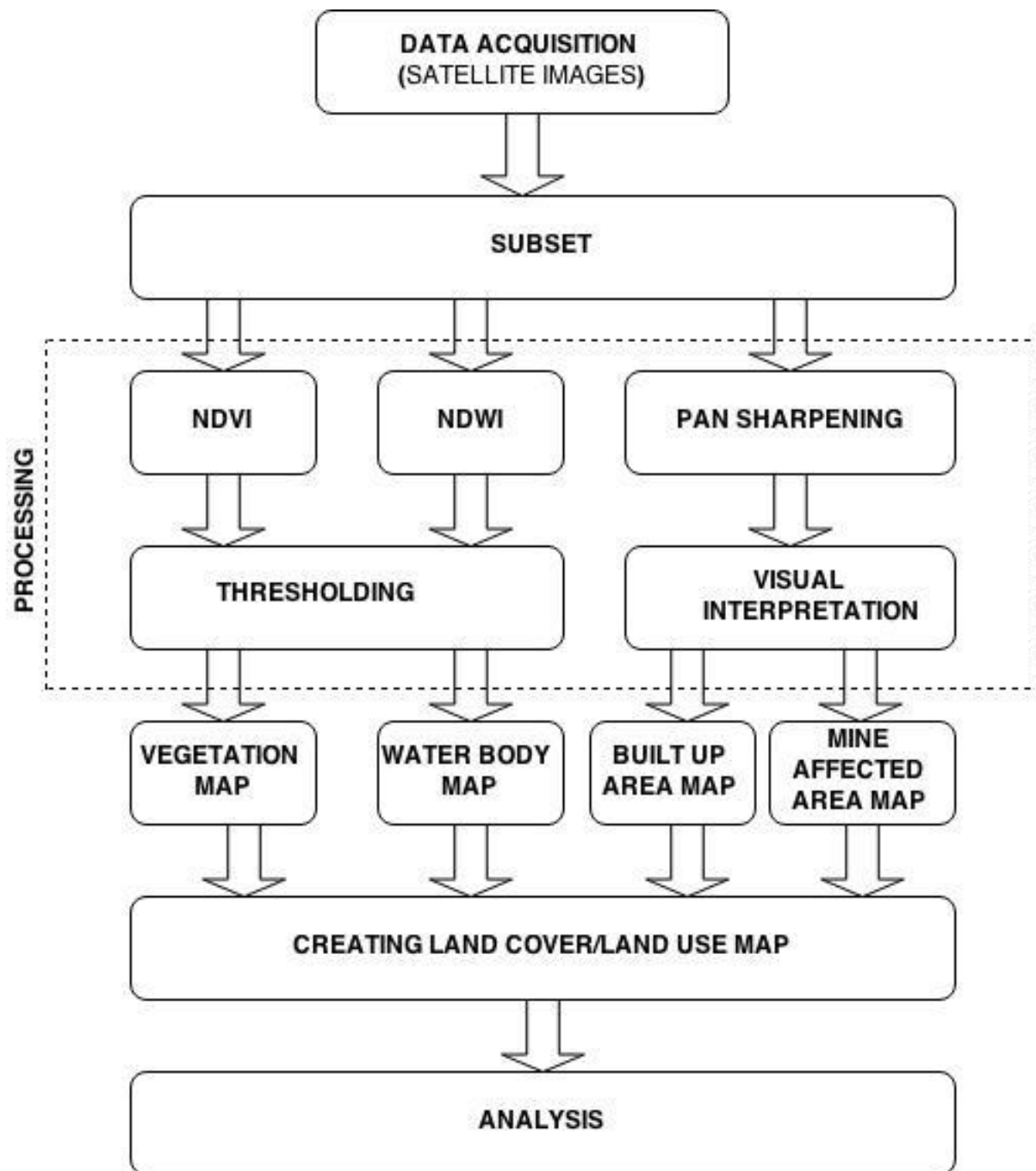


FIGURE 5.1 FLOW CHART OF METHODOLOGY

CHAPTER 06

RESULT &

DISCUSSIONS

6.1. RESULT

Figure 6.1 to 6.5 shows the Land Use/ Land Cover map of the study area generated by following the methodology mentioned in Chapter 5.

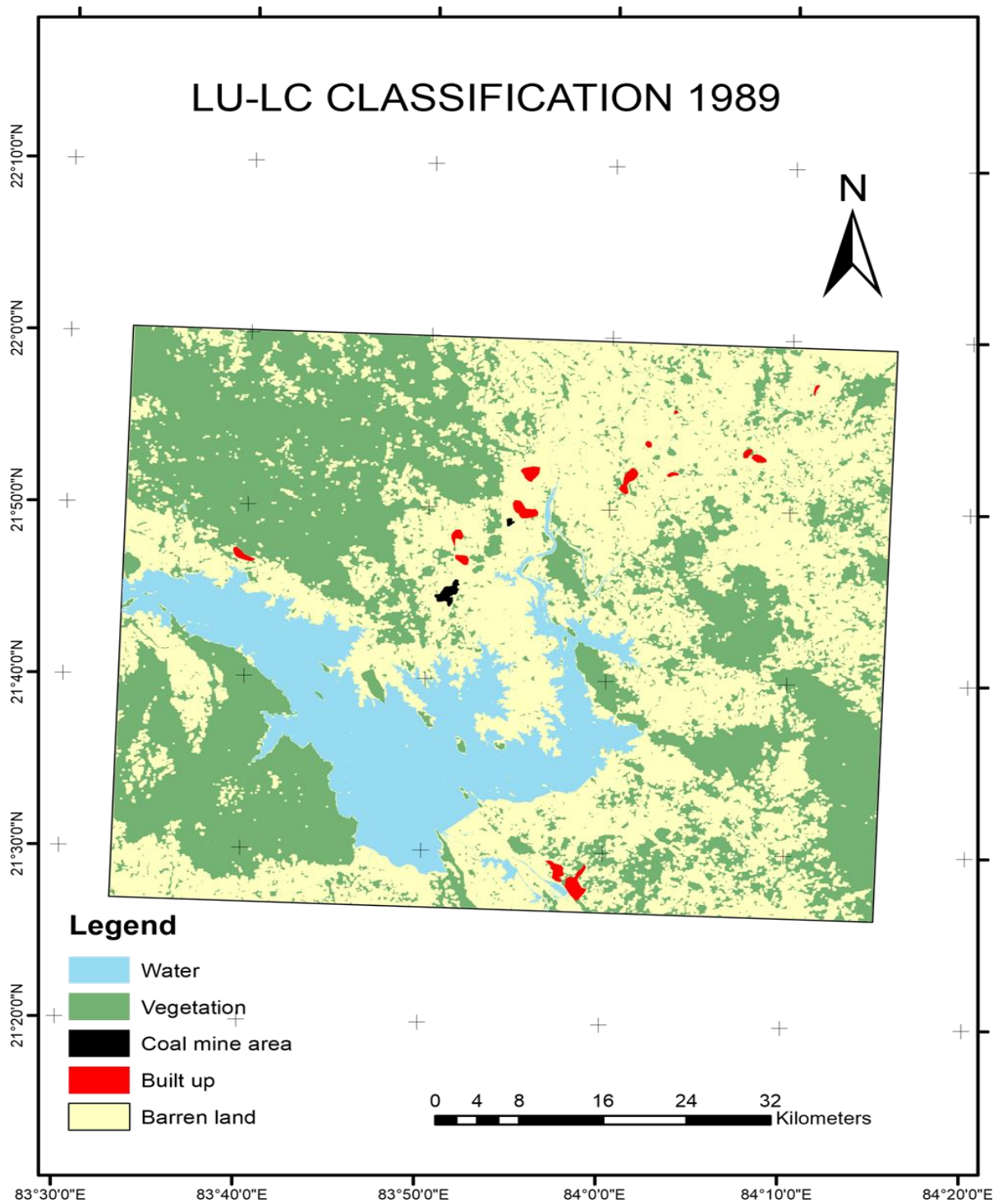


FIG 6.1 LAND USE LAND COVER MAP OF 1989

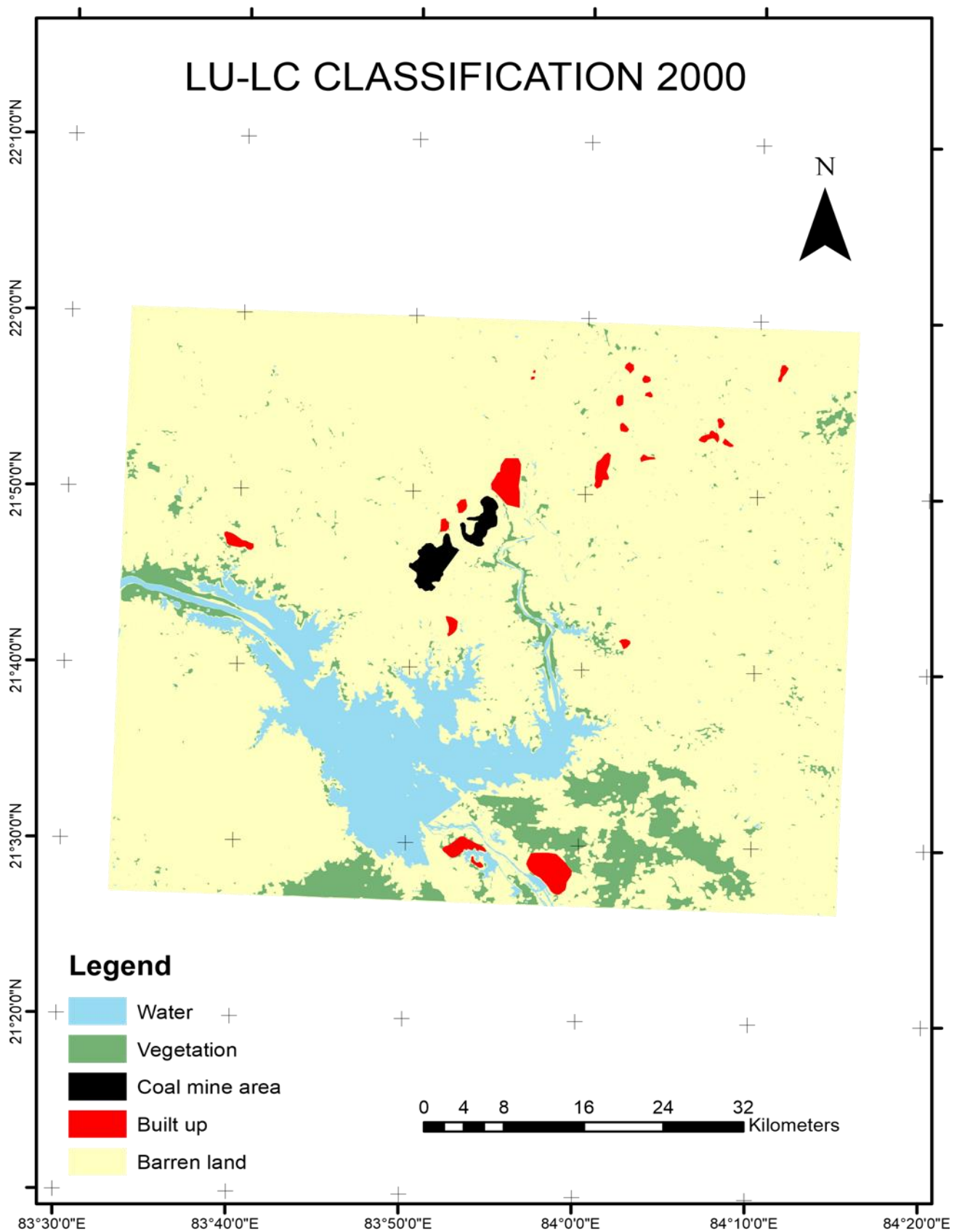


FIG 6.2 LAND USE LAND COVER MAP OF 2000

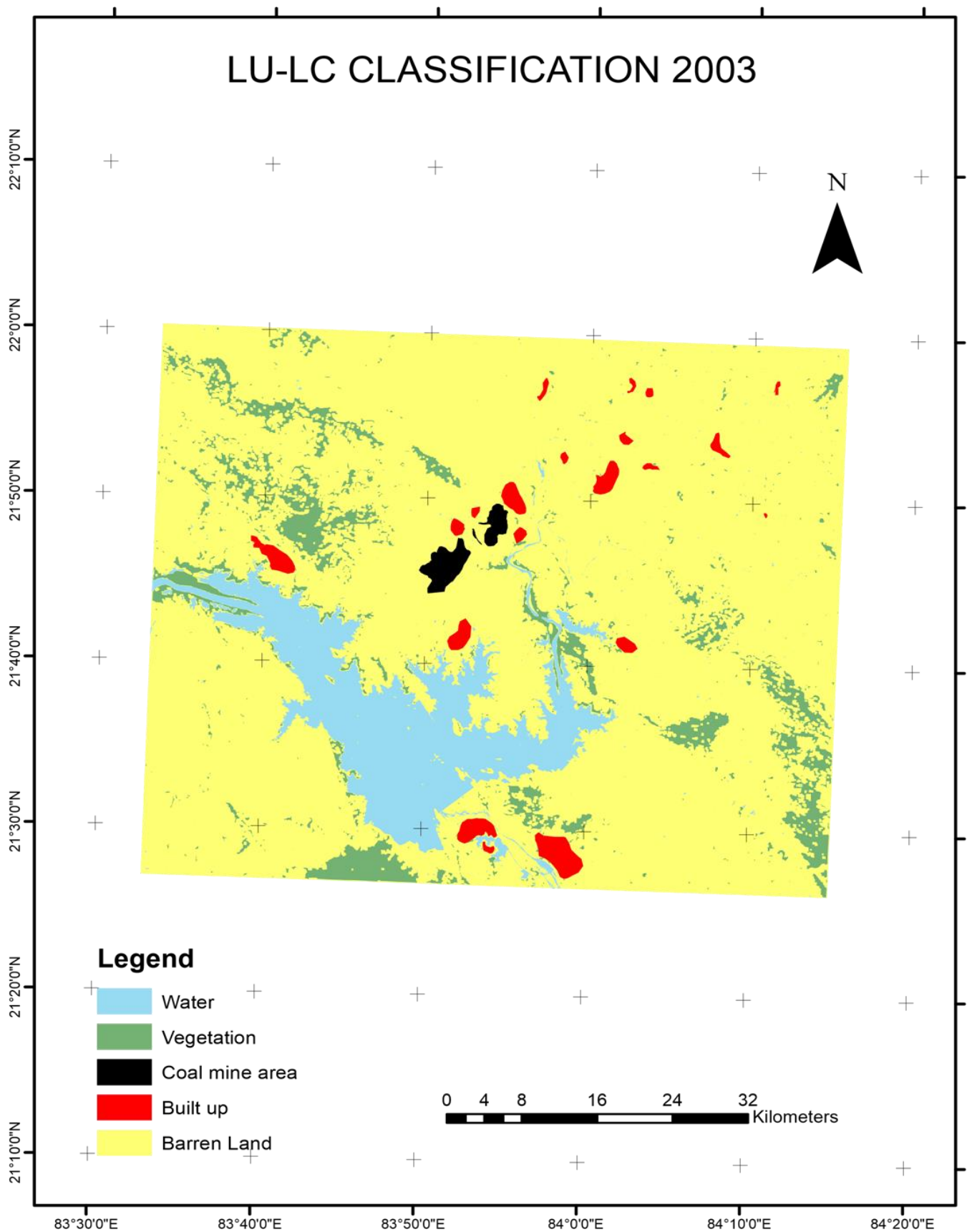


FIG 6.3 LAND USE LAND COVER MAP OF 2003

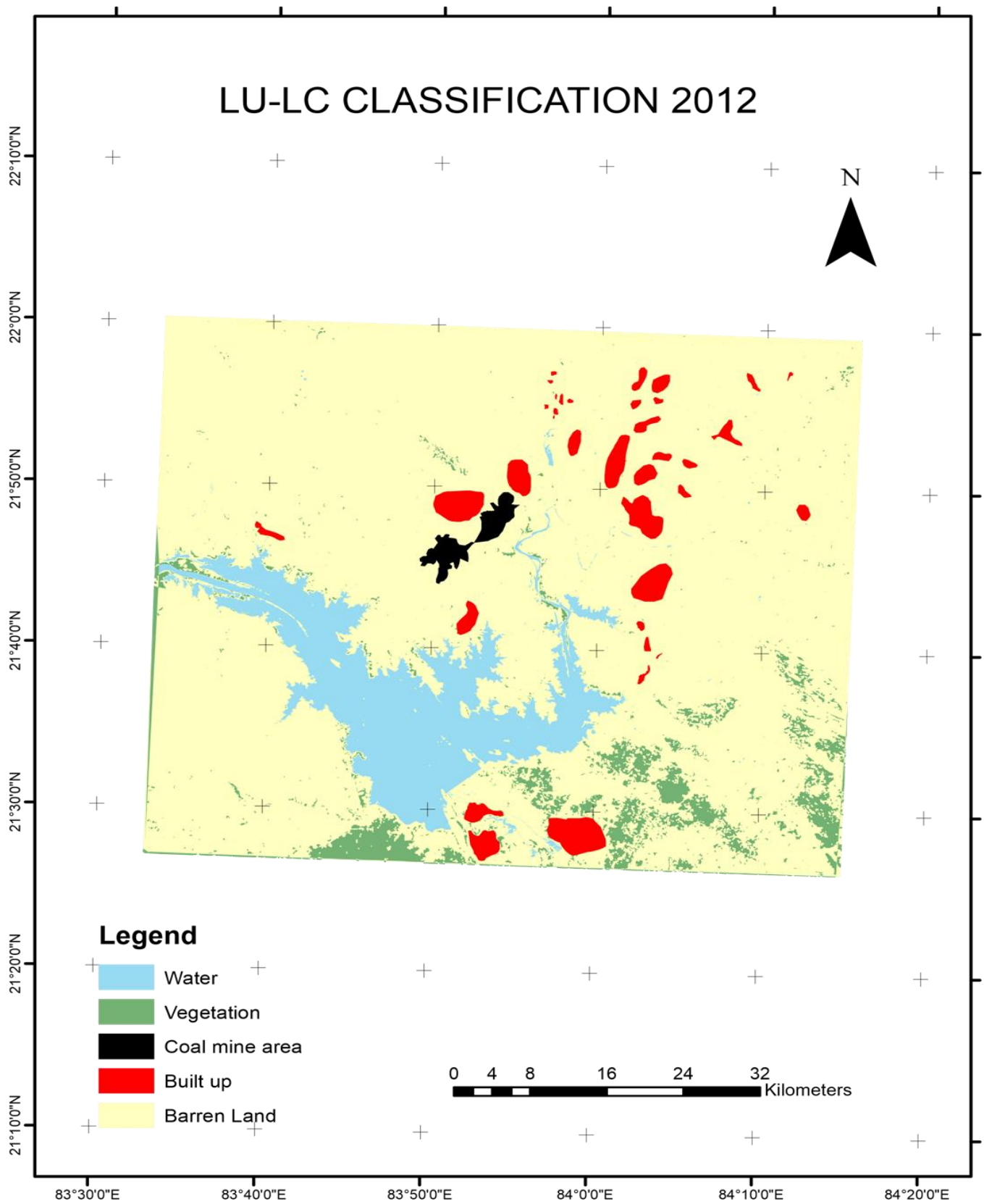


FIG 6.4 LAND USE LAND COVER MAP OF 2012

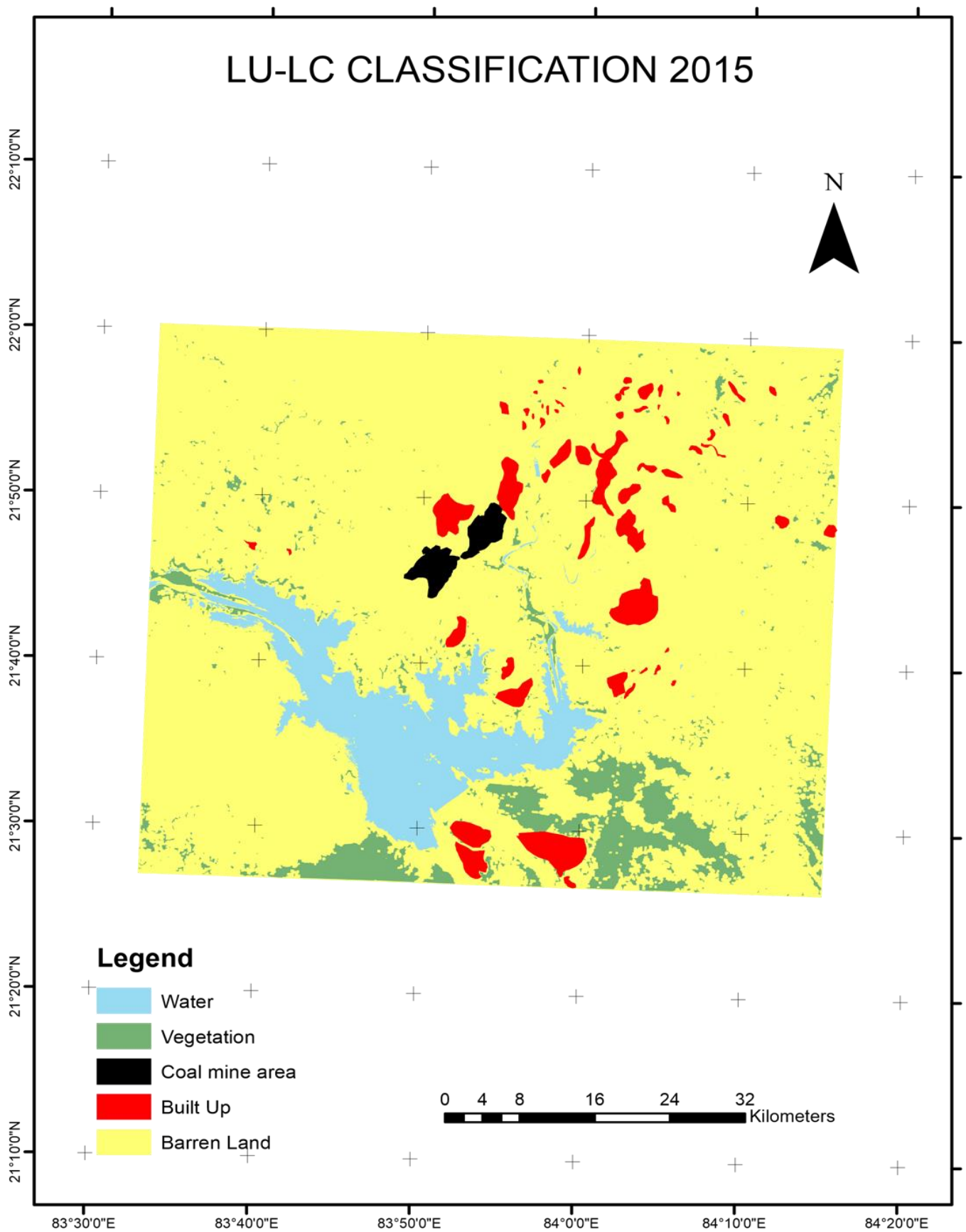


FIG 6.5 LAND USE LAND COVER MAP OF 2015

6.2 DISCUSSIONS

Table 6.1 MULTI-TEMPORAL LU/LC MAPPING & ITS STASTICAL ANALYSIS:

Land Use/ Land Cover	1989		2000		2003		2012		2015	
	Area sq.km	%	Area sq.km	%	Area sq.km	%	Area sq.km	%	Area sq.km	%
Water bodies	580.68	13.0	401.28	8.95	453.19	10.11	459.54	10.25	388.58	8.67
Vegetation	1721.44	38.4	280.3	6.25	293.24	6.54	231.32	5.16	287.62	6.4
Coal Mining	3.581	0.08	24.45	0.54	25.309	0.56	27.06	0.6	33.81	0.75
Built-up area	37.44	0.83	46.61	1.04	64.66	1.44	128.93	2.87	156.62	3.5
Barren land	2138.86	47.7 2	3729.36	83.2	3645.6	81.34	3635.15	81.1	3615.37	80.6 6

TOTAL AREA= 4482 sq.km

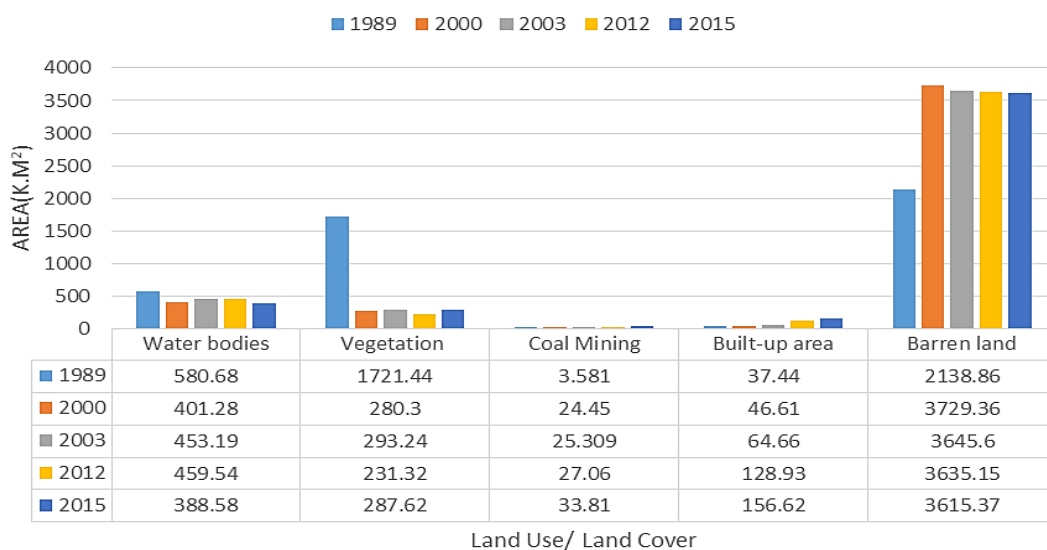


FIGURE 6.6. BAR GRAPH ANALYSIS OF RESULT

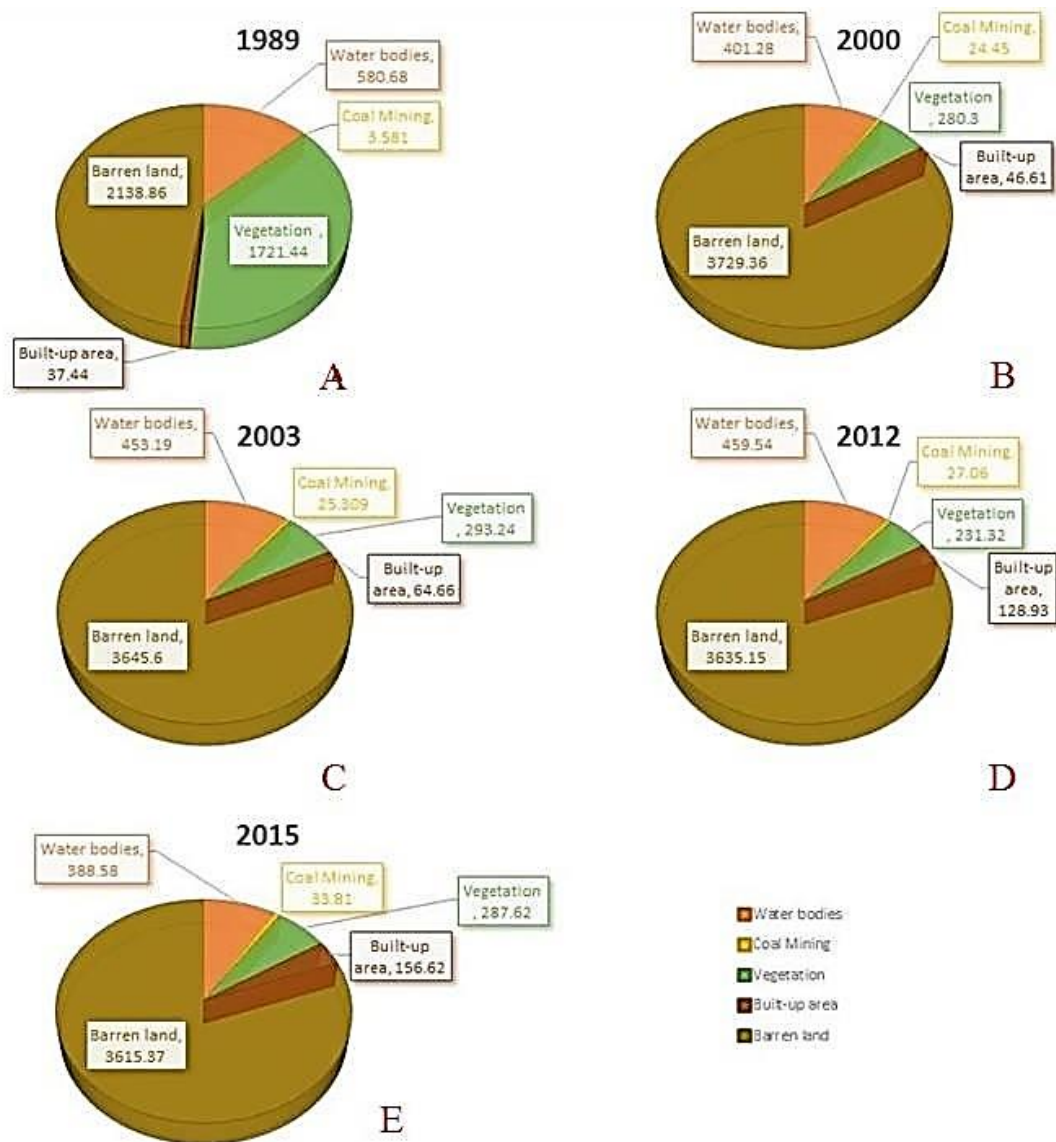


FIGURE 6.7: PIE CHART ANALYSIS OF RESULT

Fig 6.7. A-E are the LU / LC classification result of different time period. As expected maximum spatial coverage in vegetation and water bodies was observed in 1989, whereas the maximum change in spatial coverage of mining area and built-up area is in 2015. The huge difference in heavily vegetated area of 1989 is because of acquisition in the post monsoon period. The accuracy of this classification is limited to the accuracy of sensors used and the purity of pixel. Chances of mis-classification is high for a mixed pixel if there is no dominant signature.

The use of higher resolution data set will definitely improve the number of classes, but still the present work gives us an idea of the changing dynamics of land use pattern of Ib Valley coalfield.

The results as shown in Table 6.1 make it very clear that there has been a tremendous increase in the mines area from 1989 to 2015 of about 30 km² which has led to a drastic increase in settlements and a steep drop in the total forest cover. The vegetation cover has suffered a loss of about 1434 km² because of large scale deforestation caused due to mining activities and construction of settlements. The increase in mines area and industrialization of the nearby areas is the main reason for increase in the settlement area by 119 km² in-between 1989 and 2015.

The decline of vegetation cover in the region can be attributed to the increase of mining and built-up area. Actually, the rapid growth of mining activities caused increase in settlement by migration of people into the area.

The major limitation of the study is that the resolution of all the five images is not the same. The 2012 LISS III image has a resolution of 23.5m whereas other images which were acquired through Landsat have a resolution of 30m. Therefore, accuracy of results from 2012 image is better than others.

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